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Empowering customer satisfaction chatbot using deep learning and sentiment analysis

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ABSTRACT

The rapid advancement of technology holds great promise for various types of users, clients, or service providers. Intelligent robots, whether virtual or physical, can simplify the reservation process. With the development of machines and processing tools, natural language processing (NLP) and natural language understanding (NLU) have emerged to help people comprehend spoken language through machines. In order to facilitate seamless human-machine interaction, we aim to address customer needs through a chatbot. The objective of this paper is to incorporate sentiment analysis techniques with deep learning algorithms to cater to customers' needs during message exchanges. This study aims to create an intelligent chatbot to engage customers during their routine operations and offer support. In addition, it offers to companies a manner to detect sarcastic messages. The proposed chatbot utilizes deep learning techniques to predict users' intentions based on the questions asked and provide a helpful and convenient answer. A new chatbot for the customer is presented to overcome with challenges related to a wrong statement like sarcastic one and feedback towards user messages. A comparison between deep and transfer learning gives a new insight to include sentiments and sarcasm detection in the conversion process.

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1. INTRODUCTION

The evolving technologies in artificial intelligence are considered the primary helpful tool in human life [1]. The emergence of intelligent systems and their flexibility has facilitated their incorporation into websites and mobile applications. Human-machine interaction made a huge splash recently, especially during and after the COVID-19 pandemic, which introduced virtual and physical bots [2]. To prevent any direct communication or even travel to book a restaurant or flight, usually people or clients must give a call or go directly to finish the job. Evolutionary techniques, such as natural language processing (NLP) and deep learning techniques, make it easier in a manner that makes machines ensure the communication operation. Virtual assistants have been known for many years through some applications such as Apple Siri or Amazon Alexa, and others make good help for users [3], [4]. Indeed, chatbots are considered the most suitable application to facilitate machine and human communication. The revolution of social media, such as Web 3.0 and Web 4.0, spread the utilization of robot assistants, especially in commercial pages that require service the whole time [5], [6]. Moreover, the spread of information and the quantity of data with the evolution of resources given by cloud computing through their services made the development much easier to satisfy the client's demands [7], [8]. Nevertheless, in traditional communication, the user calls for service by phone or travels to some location, which may waste time. Human-to-human communication is, in fact, related to work time, which is not covered the whole day, and people may get tired from taking calls. To solve this issue, AI bots are represented as a suitable solution. Personal assistants could enhance and facilitate transactions, and it would help to propose a solution from the internet for an alternative solution in a reasonable time. The advancement of natural language treatment is the trend in the whole market, as shown by Bard of Google or ChatGPT for OpenAI [9], [10]. However, these solutions are not the best for personal websites and private companies. Any company should try to use its receptionist AI bots to respond to clients' requests. Moreover, processing natural language is a challenging problem due to the significance and meaning of the words used in each situation (the same word has many definitions). To study this problem, the most appropriate solution is to use AI solutions such as ontologies, semantic-based solutions, and others [11], [12]. However, these methods are not good enough to respond to the client's requirements quickly and make an accurate response due to the complexity of the treatment. Deep learning and transfer learning have leaped to understand natural language [13], [14]. One more critical problem related to misunderstanding messages such as related to ironic or sarcastic ones as used in social media messages. Behavioural profile is messing in previous chatbots, this problem can detect the sequence chain of messages which link it to the user's sentiment. In the literature, over the past few years, human-machine interaction has evolved with the advancements in NLP and deep learning techniques. Actually, several works have been conducted to develop virtual or physical bots using robots or augmented reality avatars. Chatbots have been widely explored in various domains, including tourism, healthcare, education, and customer service [15]–[21]. Specifically, in the context of customer service, Ngai *et al.* [18] proposed a chatbot-based solution based on a dedicated knowledge-based design framework. The framework incorporates customer knowledge management (CKM) and utilizes a web crawler to collect data from the internet, thus improving the chatbot's knowledge base. Tran *et al.* [19] investigated the impact of chatbots on consumer behavior in different retail sectors, with a primary focus on the fashion and telecom industries. They combined a VADER lexicon-based classifier with a Naive Bayes classical machine learning model to examine customer sentiment towards chatbots and online human agents, particularly on Twitter. Chung *et al.* [22] analyzed customer data related to chatbots, particularly in the context of luxury fashion retail brands. They employed five different models to measure customer perceptions of chatbot interactions, entertainment value, customization, and problem-solving. Their study provided insights into how chatbots influence luxury customer feedback and satisfaction. Sperlí [15] introduced a framework designed to assist tourists during their journeys. This framework integrates intangible and tangible cultural objects into a unified data model and utilizes a seq2seq model to generate answers. It also offers information about events or suggests visit paths. Dharani *et al.* [23] addressed the challenges faced by passengers in public transportation, particularly when navigating unfamiliar locations. They developed an interactive chatbot that provides information about buses and their operating schedules, simplifying the process for passengers to utilize and communicate at any time or location. The chatbot utilizes long-short term memory (LSTM) for text classification and selects responses from a database of previous answers. Oguntosin and Olomo [24] created a chatbot for Covenant University shopping mall, aiming to provide intelligent, accurate, and real-time conversations with students. The chatbot allows students to communicate and inquire about specific items they want to purchase online. It is accessible through different devices, providing 24-hour online service. They utilized the Seq2seq model for feature extraction and sequence output. Xu *et al.* [25] developed a conversational system for customer support using a sequence-to-sequence model with an encoder and decoder based on LSTM neural networks. The model was trained on a Twitter conversation dataset, and upon receiving an input request, it generates a response.

However, all the previous mentioned works does not consider some issue related to person profile can change the conversation from client to another which represented as critical issue in such application. In addition, incorporating sentiment in conversation it is in fact big challenges when we talk about the nature of sentences and messages. Obviously, many users exchange messages with hummer manner especially in such application for fun as social media which could lead to misunderstanding during conversation. These sarcastic and ironic messages challenges are the difficult to detect using previous chatbot. The paper aims to solve the problem by proposing an AI bot model using deep learning techniques for intent recognition and classification. With retrieval information, the chatbot could help the user get an accurate answer in a reasonable time. Another issue related to customer communication, especially in order operations, led to the cancellation of orders, which may reduce the company's efficacy and reputation. To solve the mentioned issue, our solution is to construct a generative response using sentiment analysis to ensure a good understanding of the customers' mood through a question/answer application to gain the client's trust. Most of presented works does not focus on sentiment during conversation. One more critical matter related to sarcastic or ironic message detection which is a big challenge, which could lead the conversation accurately and satisfy both clients and market. The proposed framework has the following benefits:

– A sarcastic and ironic message detection during conversation.
– Feedback generator using user historical conversation and social media dataset.
– Sentiment analysis to increase answer precision.
– Comparison of deep learning and transfer learning for sentiment analysis and sarcastic detection chatbot.
– Voice and text-based answer chatbot with multilingual option (English, Arabic, and French).

The present paper is organized as follows: section 2 describes our proposed framework with the used method. Section 3 provides some discussion about the obtained results. Finally, section 4 concludes this paper.

2. PROPOSED METHOD

The evolution of artificial intelligence techniques has led to the development of personal assistants, which are becoming increasingly popular in the form of virtual and physical question-answering systems. ChatGPT and Bard are examples of systems designed to retrieve information from vast knowledge banks, but private companies often prefer to have their own customized solutions. Communication plays a crucial role for companies, particularly those with customer services, and it is essential to build a robust application capable of handling various user queries beyond just frequently asked questions. Language processing can be complex, even in human-to-human communication, so automating the task with machines presents its own set of challenges. Among the challenges resolved in this paper is the problem of understanding sarcastic and ironic messages that are often noisy for company. One more critical thing is related to feedback that might enhance both the company and customer satisfaction in the future. Whereas sentiment is interesting in such use, studying every statement is to difficult using a machine. The present solution presented in the following framework (see Figure 1).

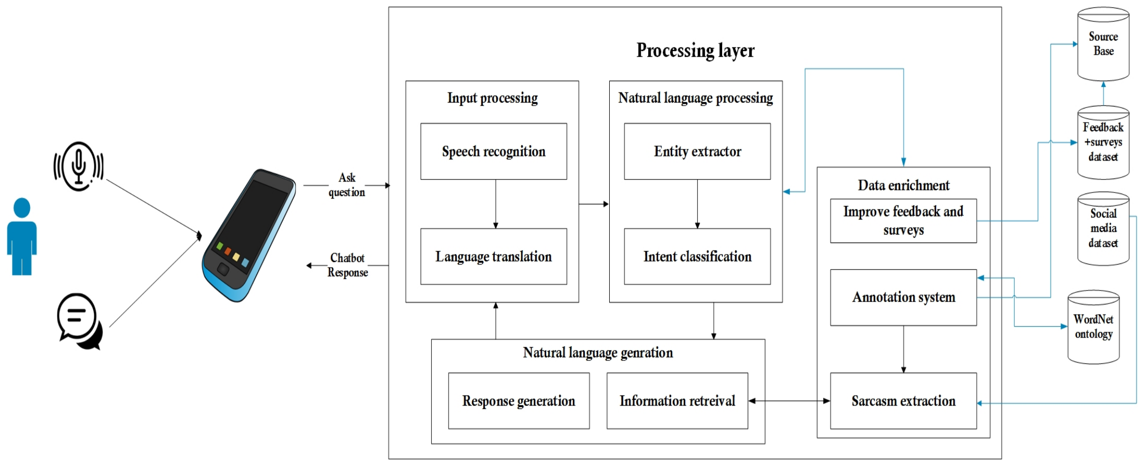

Figure 1. Overview of chatbot framework for customer satisfaction

The proposed framework for chatbot relies on a trained model to provide responses to client inquiries. Retrieving the appropriate response from a vast dataset poses a significant challenge. In this paper, we propose a chatbot that leverages multiple deep learning models to accurately select the correct answer for user queries. Additionally, our chatbot has the capability to respond in three different languages and can also provide speech-based responses to cater to the needs of visually impaired individuals. In our proposed solution, the chatbot takes the user's sentiment into account in order to deliver personalized and satisfactory responses, ultimately contributing to increased profitability and reputation for the company. Moreover, it helps to detect sarcastic messages since are disturbing at the company level.

2.1. Data pre-processing and normalization

Pre-processing is a crucial step in constructing models using machine learning or deep learning techniques. Its main objective is to make the data more manageable and enhance the model's accuracy for classification. The quality of the data is paramount in determining the effectiveness of this step. The following steps are performed during each model construction phase:

- Removal of stop words, punctuation, and undesirable symbols.
- Tokenization, stemming, and one-hot encoding.
- Reducing word variation by converting all words to lowercase.

Therefore, our data pre-processing methods aim to represent each sequence with an integer representation of the same length as the vocabulary size (number of unique words) in the dataset. This vectorization process simplifies the training and building of the NLP model. In this chatbot, we utilize an open-source Kaggle dataset [26] that includes a collection of 27 intents grouped into 11 categories related to the ”customer support” domain. These intents were extracted from Bitext's 20 domain-specific datasets while retaining intents that are relevant across different domains. The dataset provides information on intents, categories, and languages. Also we used another sarcastic dataset [27], consists of 28,619 tweets tagged with 0 for not sarcastic and 1 for sarcastic.

2.2. Chatbot customer assistance process

In this subsection, we introduce the used models and the whole process used in the framework especially sentiment analysis and sarcasm detection.

2.2.1. Training models

Our proposal utilizes two types of deep learning and transfer learning. The first two models employed are LSTM and Glove_LSTM, which are unsupervised learning algorithms used for word representation [28]. LSTM is a recurrent neural network that requires multiple steps to reduce errors and improve the accuracy of question responses [29]. Initially, we utilize the pre-constructed one-hot encoded sequence to train our intent classification prediction model. Creating an accurate model is crucial, especially for deep learning models. To achieve this, we need to determine the optimal configuration, including the number of LSTM cells, layers, and activation functions. Finally, we test and validate the model using predictions. The LSTM model addresses these challenges by learning when to forget and when to utilize gates (similar to basic neural network gates, but with three gates: input, forget, and output gates refer to Figure 2). The input gate determines which values should be stored in memory, the forget gate determines which data should be discarded, and the output gate determines the state modification to compute the output for the current timestamp. The architecture of an LSTM cell (see Figure 2) can be described as (1) to (5) [30]:

$$Input\ gate : i_t = \sigma(w_i.[h_{t-1}, x_t] + b_i) \tag{1}$$

$$Forgot\ gate : f_t = \sigma(w_f.[h_{t-1}, x_t] + b_f) \tag{2}$$

$$Output\ gate : o_t = \sigma(w_o.[h_{t-1}, x_t] + b_{fo}) \tag{3}$$

$$Cell\ state : c_t = f_t \times c_{t-1} + i_t \times tanh(w_c.[h_{t-1}, x_t] + b_c) \tag{4}$$

$$Cell\ output : h_t = o_t \times tanh(c_t) \tag{5}$$

Where w_x represents the weight for the respective gate(x) neurons, h_{t--1} is an output of the previous LSTM block, x_t is input at the current timestamp, and b_x are the biases for the respective gates(x).

The third model, bidirectional encoder representations from transformers (BERT), is a pre-trained language model that utilizes transfer learning. This approach is gaining widespread recognition in the field of NLP and is gradually becoming an industry standard. BERT stands out for its ability to capture and extract contextual meaning within phrases or texts. Unlike traditional word embedding models, BERT considers the surrounding words and context to determine the numerical representation of a word or token during the concept embedding process. This contextual understanding enhances the model's ability to comprehend the syntax and semantics of a text [31].

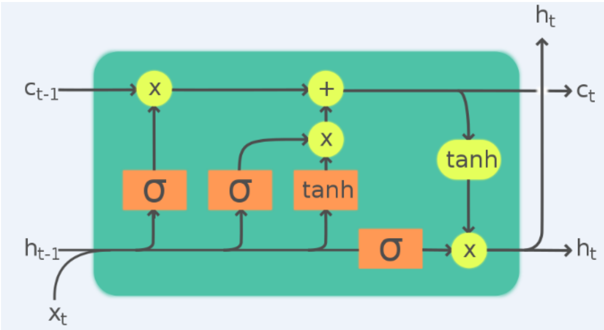

Figure 2. Inter LSTM cell architecture

In order to respond to the users' questions, the proposed customer assistance comprises a set of steps illustrated in the subsequent flowchart (see Figure 3). Our chatbot is designed as an information retrieval system to provide accurate responses. The steps involved in our solution are depicted in Figure 3.

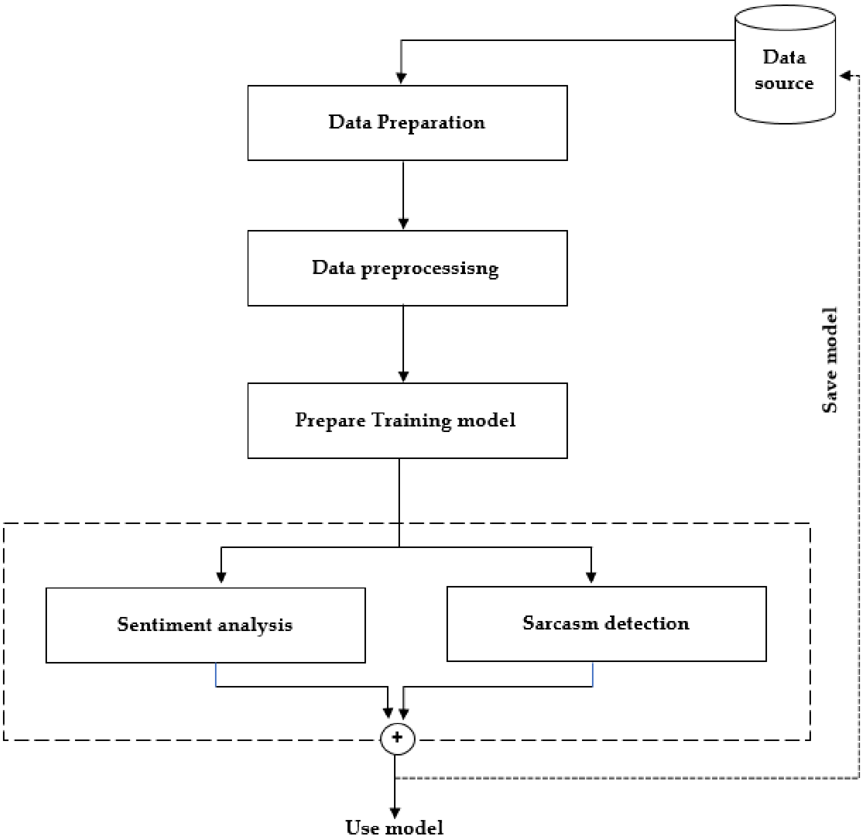

Figure 3. Chatbot customer assistance process

– Data preparation: this step refers to data enrichment in our framework, at this stage we apply data enrichment towards existed data to add specific information using techniques for the purpose of enhancing it. The first method is tf-idf along with WordNet ontology to annotate texts in dataset [32]. We incorporate sentiment labelling using one-hot encoding sequences [33]. This enables the model to analyze the input and categorize the sentiment into three classes: positive, negative, or neutral, enhancing the understanding of the conveyed sentiment in the text. The same thing for sarcasm labeling using social media dataset.
– Data preprocessing: refers to steps explained in subsection 2.1. for the purpose of coding data (word

embedding) to feed them to DL and TL models.

– Prepare training model: to prepare the training model for classifying intentions based on the previously explained dataset, this step is crucial. The employed deep learning techniques, namely BiLSTM and Glove_LSTM, rely on specific settings to create the best model. We define various parameters, including dropout rate, number of epochs, learning rate, batch size, optimizer, and loss function. In case the model fails to deliver satisfactory or accurate results, we iterate through this step, experimenting with different parameter combinations until we enhance evaluation metrics such as F1-score, recall, and accuracy.
– Sentiment analysis: after configuring the settings and performing intent classification, the next step involves annotating the texts in the dataset using WordNet. Additionally, we utilize a dataset that has been labeled with positive, negative, and neutral sentiments. To accomplish this, we employ both BiLSTM and Glove_LSTM models. Subsequently, we can either save the annotated texts for general messages or disregard them as needed.
– Sarcasm detection: deep learning techniques are instrumental in detecting patterns in text. It is crucial to identify the direct meaning of a message, making sarcasm detection essential for customer chatbots to instil trust and save time. In our framework, we trained our model to distinguish between sarcastic and non-sarcastic messages. These messages resemble those commonly used on social media for humour or to annoy someone, which is not suitable for this context. The BiLSTM model was trained using a dataset to create a capability for identifying such messages. Our framework generates a general response in such situations, offering a rephrased response or suggesting a different question.

Towards the conclusion, once we have minimized the model's errors and improved its accuracy and precision, we proceed to save the trained model. Subsequently, we can integrate it into our chatbot. Furthermore, our framework has the capability to enrich its dataset through surveys and feedback gathered from users. Then we combine both models to obtain a model able to detect sarcasm and handle sentiment as well. The next (see Table 1) explains the used configurations train the used models BiLSTM and Glove_LSTM.

Table 1. Hyperparameters settings

Parameters	Values
BiLSTM output size	20
Dropout	0.3
Epoch	20
Learning rate	0.001
Batch size	128
Validation split	0.2
Loss function	Cross-entropy
Optimizer	0.90

2.3. Evaluation metrics

Evaluating models requires calculating some measures after training and validation to see if they are ready to use. Performance evaluation included accuracy, precision, recall, and F1-score [34], [35]. This subsection describes evaluation metrics: TP, TN refers to true positive and negative, whereas FP, FN refers to false positive and negative. Precision, recall, and F1-score, based on the parameters provided, are expressed in (6) to (9):

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \tag{6}$$

$$Precision = \frac{TP}{TP + FP} \tag{7}$$

$$Recall = \frac{TP}{TP + FN} \tag{8}$$

$$F1 - score = \frac{2 \times (precision \times recall)}{precision + recall} \tag{9}$$

3. RESULTS AND DISCUSSION

This section presents some experimental results which are obtained from used models, then we analyze the obtained results with some discussion related to proposed framework for customer chatbot purposes. As mentioned in the previous section, this paper utilizes deep learning models, specifically BiLSTM and Glove_LSTM, to predict user intent and address their concerns. In addition to these models, we also employed transfer learning using the BERT model. To compare the performance of these models, in our experiments we have used two ideas: i) the first one we just implies intent classification using sentiment with three models and ii) where the second consists of combining two models for sentiment analysis and sarcasm detection only with BiLSTM and Glove_LSTM. Our obtained results presented in the following see Table 2. Figure 4 explains the confusion matrix of the proposed framework (Figure 4 left one) after constructing the model for intention classification with sentiment. From this figure, the model provides a good solution suitable for any intention and can predict the right intention from the user question.

Table 2. The performance results

	Intent classification			Sentiment and Sarcasm detection	
Metric	BiLSTM	Glove_LSTM	BERT	BiLSTM	Glove_LSTM
Accuracy	0.90	0.94	**0.997**	0.92	**0.96**
Recall	0.90	0.96	0.99	0.70	0.77
Precision	0.94	0.99	0.99	0.90	0.93
F1-score	0.90	0.98	0.99	0.79	0.85

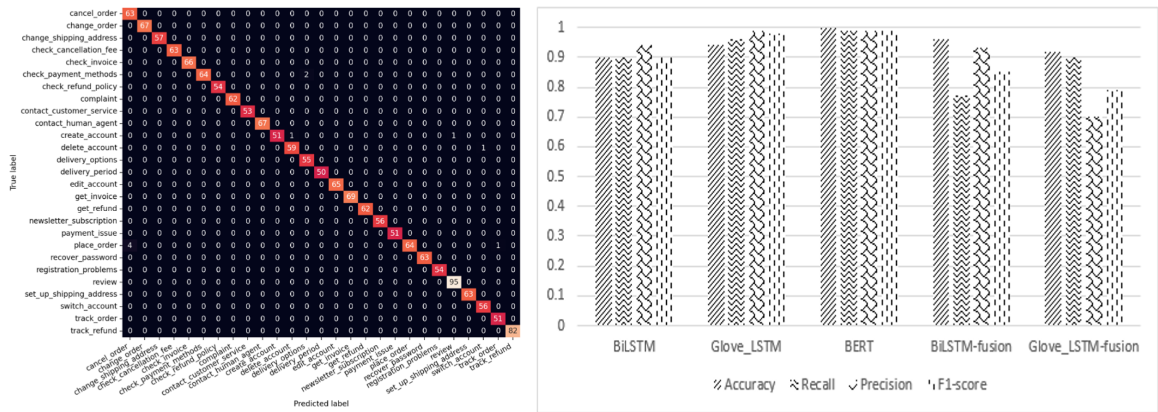

Figure 4. Confusion matrix and evaluation performance results

In this paper, we present a customer assistant bot that assists users with their questions, considering their sentiments. As discussed in previous sections, our chatbot is constructed using three different models. As shown in Table 2, the BERT model performs well across various metrics. This can be attributed to its pre-training on a large dataset, although fine-tuning the model settings was necessary to achieve these results. In the case of the deep learning models, BiLSTM and Glove_LSTM, we observe different outcomes compared to the BERT model because these models were built from scratch. BiLSTM, which is based on a recurrent neural network, is well-suited for this problem as it can comprehend the context and semantics of sentences and documents, leading to reliable F1-score results. On the other hand, Glove_LSTM utilizes global vectors to represent and encode words, aiding in the processing step. This technique also helps in reducing the number of words, which significantly impacts sentiment detection from user queries. To measure the loss value in these models, we employ a categorical cross-entropy function, which is commonly recommended for classification problems. Furthermore, some of these models require addressing issues of underfitting and overfitting. To mitigate these problems, we introduced a different activation function in the last layer, specifically the dense layer of the model. For the second method, which provides a fusion between two BiLSTMs (Glove_LSTM for comparison) models for both sentiment and sarcasm, we can observe from Table 2 (presented in Figure 4 as BiLSTM-fusion and Glove_LSTM-fusion) that it yields good results in accuracy. However, the F1-score decreases due to the occasional confusion between sentiment and sarcastic messages, which can be semantically similar in some instances. To address this issue, we can consider combining multiple models to improve the overall performance. Overall, our approach demonstrates the effectiveness of utilizing various models and techniques to construct a customer assistant bot that takes user sentiments into account and provides accurate responses. Adding some experiments from social media to detect sarcastic messages will help to ensure a good quality of responses.

4. CONCLUSION

In this paper, we have presented a framework that can handle the process of exchanging messages with the clients in automatic manner. The proposed framework able to respond to clients taking into account the sentiment and sarcasm in messages. As we have seen deep learning approach that addresses the challenge of information retrieval for answering user queries on commercial websites more suitable. NLP poses complexities, and finding appropriate responses can be a daunting task. However, advancements in AI techniques, particularly deep learning and transfer learning, have played a significant role in assisting companies in developing applications that provide support anytime and anywhere.

In our study, we focused on incorporating user sentiments including sarcasm detection into our chatbot to ensure meaningful responses. By extracting sentiments from user queries, we can select the most suitable response. Moreover, our chatbot offers easy accessibility through text-based input or voice messages, enhancing the user experience. Additionally, it is designed to handle client questions in multiple languages, further expanding its usability. Identifying the correct question intention remains a challenge, but deep learning and transfer learning techniques have proven to be efficient and effective in this regard. Our paper compared several techniques for both expirements only sentiment and both sentiment and sarcasm, including BiLSTM, Glove_LSTM, and BERT, with promising results in terms of evaluation metrics. Notably, BERT, with its pre-trained model on a large dataset, outperformed the other models. Yet, the fusion of two models is considered a big challenge as we have seen in the previous section due the nature and ambiguities of concepts between sarcasm and sentiment.

For future work, we aim to incorporate additional models, particularly those involving sentiment analysis with transfer learning, to further enhance our chatbot's capabilities. Additionally, we plan to explore fine-tuning approaches to reduce training time, a crucial consideration in natural language processing tasks. These endeavors will contribute to the continuous improvement and advancement of our chatbot application.

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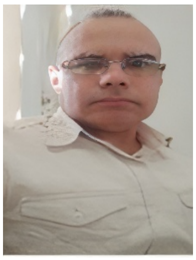

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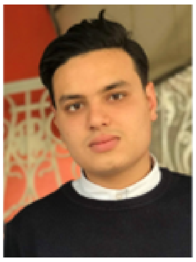

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